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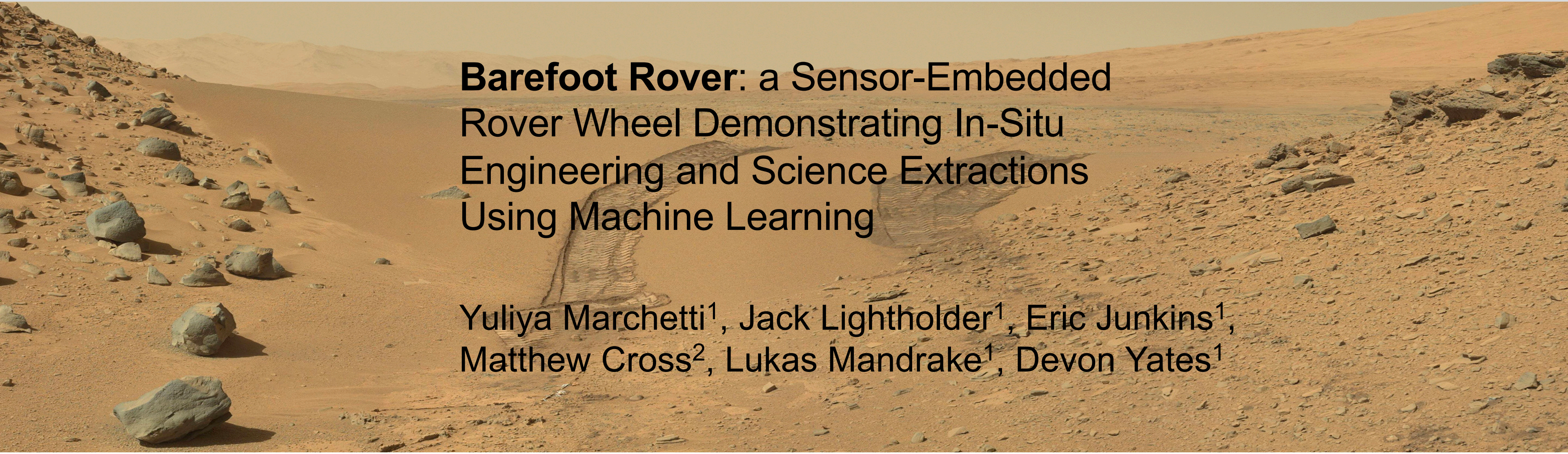

Barefoot Rover: a Sensor-Embedded Rover Wheel Demonstrating In-Situ Engineering and Science Extractions Using Machine Learning

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Outline

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- Summary of methods
- Hardware and sensors
- Machine learning:
  - Sensor data extractions
  - Featurization
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- Summary and future directions

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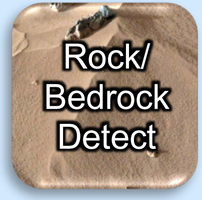
Motivation

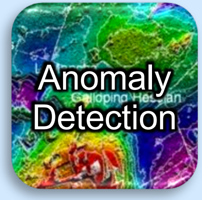
Combine in-situ sensors on a wheel and machine learning (ML) to:

- Add a sense of touch to the visual odometry
- Deploy onboard in near-real time to generate important engineering and science products
- Provide feedback to autonomous systems

Engineering, safety, stability products



Science and high-level products



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Summary of methods

The main methods and goals of Barefoot Rover:

- Use hardware to collect data from in-situ sensors for various configurations of terrain, materials, slip, hydration, composition.
- Pre-process the collected data to extract meaningful representations, e.g. images.
- Build and train machine learning models using metrics/features computed based on the representations:
  - Slip regression
  - Rock binary and terrain types multi-class classifier
  - Hydration multi-class classifier

Various data collection experiments: rocks, pebbles, sharp landforms, dunes, various compositions.

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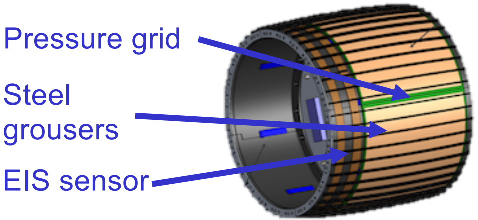
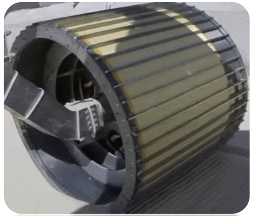
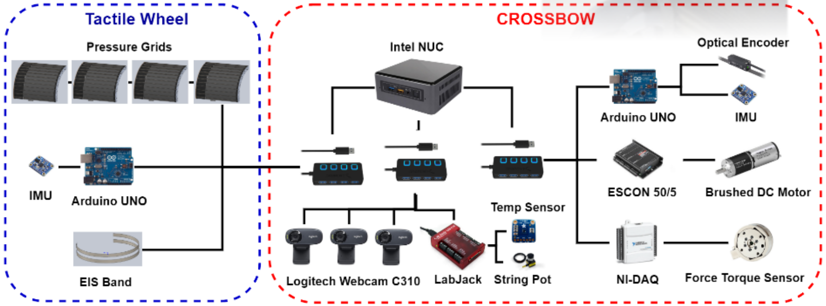
Hardware and sensor payload

Main Barefoot Rover hardware components:

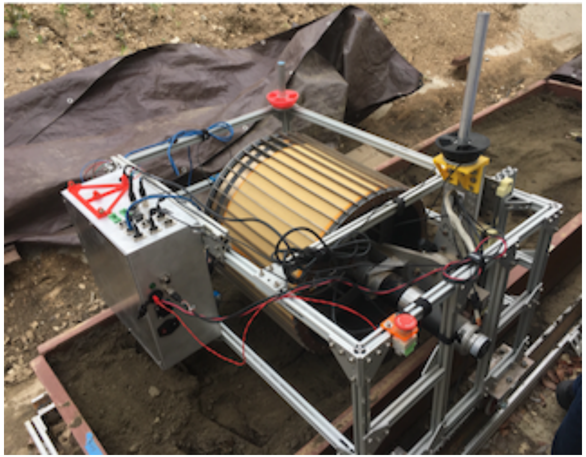
1) **Tactile wheel** carries two main in-situ sensors:
   - 2D Xiroku pressure sensor (PS)
   - Electrochemical Impedance Spectroscopy (EIS) sensor







2) **CROSSBOW test cart** allows mobility and data taking:
   - Motor, force/torque, string potentiometer



Tactile wheel is mounted on the CROSSBOW cart to be used in experiments

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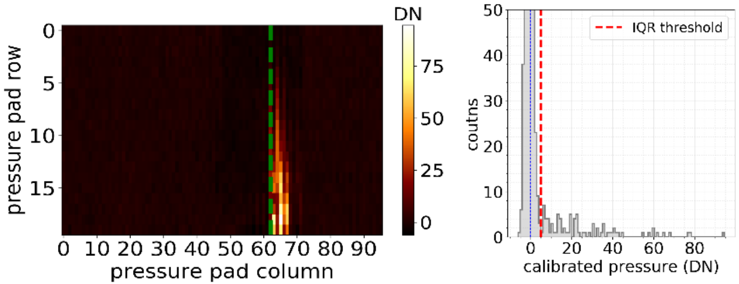
Extractions I: contact area time series

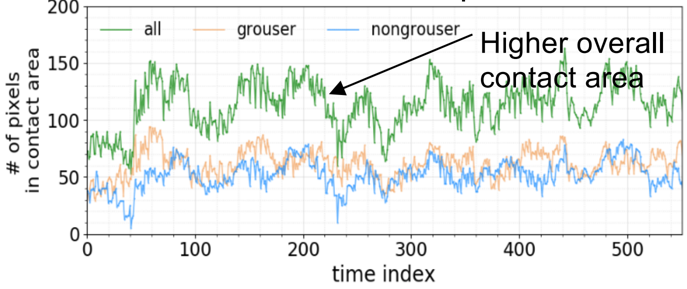
Contact area time series is one of the two extractions from the raw pressure sensor data:

- Contact area is the number of pixels in the area that is touching the ground.
- Obtained with thresholding via Interquartile Range (IQR) of the pressure values for each reading of the pressure sensor.
- Can differentiate among terrain types.

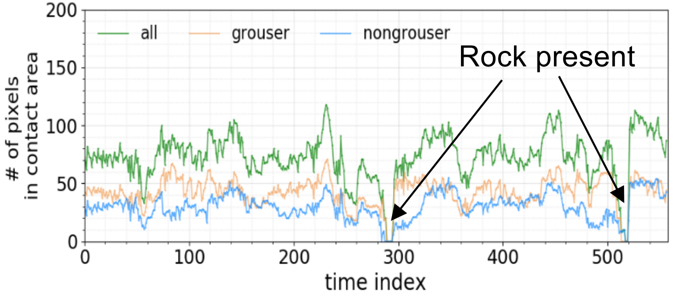


Left: pressure sensor calibrated image (20 x 96 pixels) with IMU gravity vector down (green), **right:** histogram of pressure values and a threshold for the contact area cut off (red dashed line).

Moderate slip



Rock



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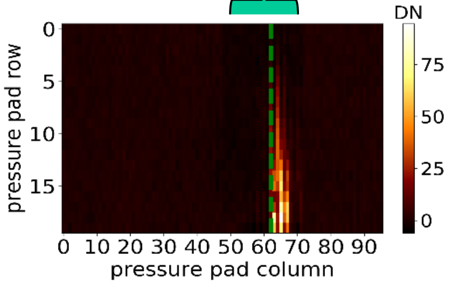
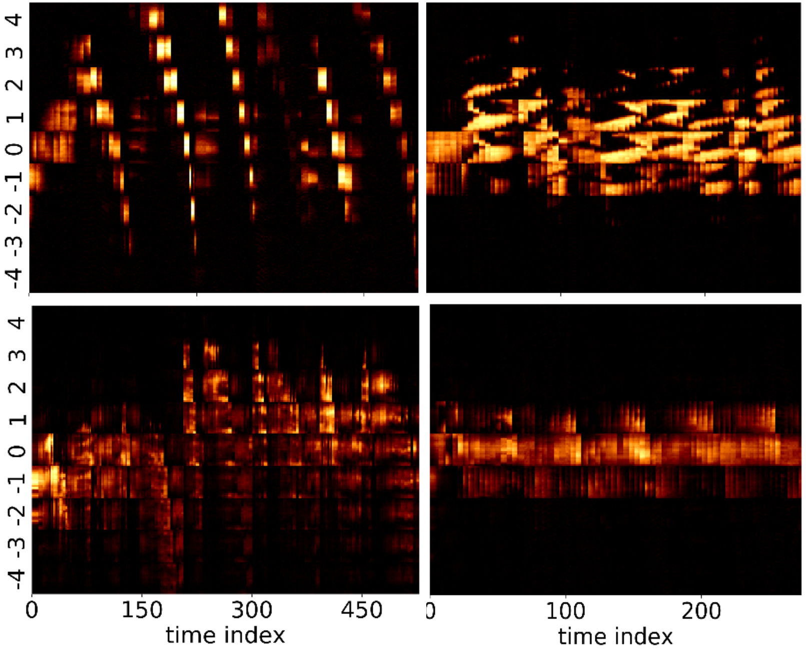
Extractions II: pressure grid images

Pressure grid **"unwrap" images** are the second pressure sensor extraction:

- They represent the spatial and time dimension of the wheel.
- The rows of pixels around Inertial Measurement Unit (IMU) are stacked as vectors for each time step.
- Unique visual signatures for various terrain states.





From left to right and top to bottom: images of **rock, dunes, slip, flat** experiments. The rows of the pressure sensor are stacked as one vector on the y-axis, with 0 corresponding to the row that aligns with the IMU reading at that point in time.

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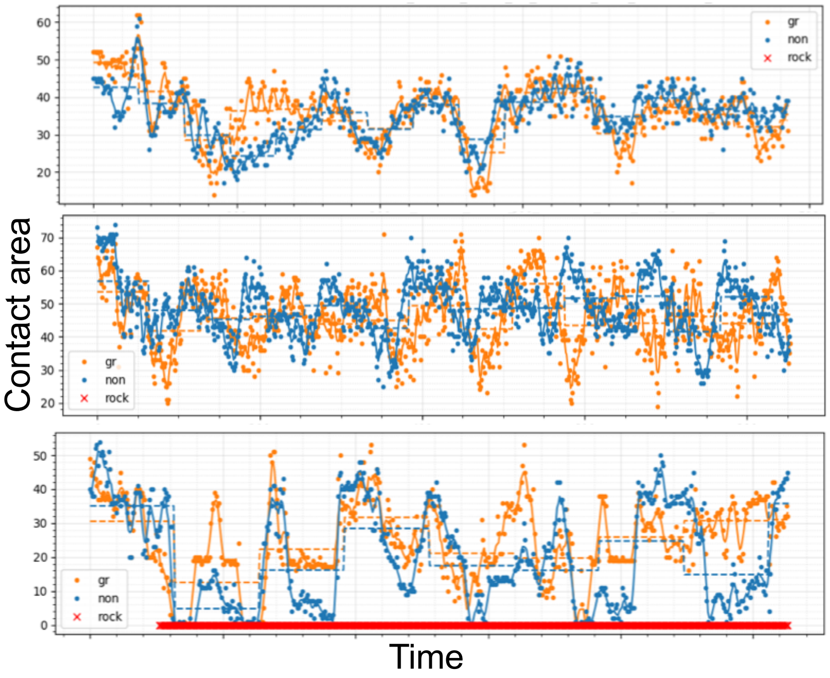
Feature extraction for ML models

Features are extracted to be the input into the ML models:

- Sliding window for streaming implementation.
- Contact area times series:
    - Signal processing, e.g. wavelets, rolling statistics
    - Time series metrics
- Pressure grid images:
    - Statistics in the spatial dimension of the wheel
    - Geometric features from derived image objects
- Grouser and non-grouser pixels carry additional information.



Contact area time series for **low slip/flat**, **high slip, rock** (top to bottom) contact area with wavelet and mean filter smoothing. Each type of experiment has a unique signature.

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Results: slip and rock

Two main ML models trained with Gradient Boosted Trees are:

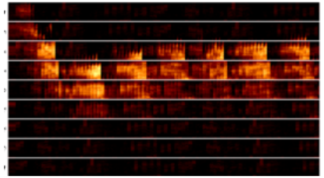
Slip regression model:

- Test root mean squares error (RMSE) -- **8.5%**
- Bias for higher slip values
- Better than current post-hoc estimates with 10% error

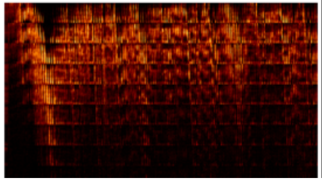
Rock binary classification model:

- Overall test accuracy -- **99%**
- Rock accuracy -- **85%**
- Buried rock accuracy -- **7%** but obtained rock likelihoods are larger than for the flat experiments

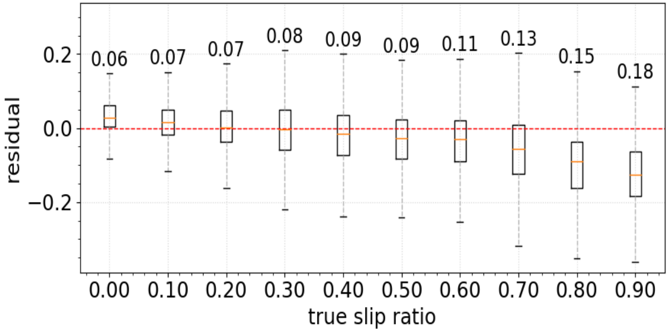
Low slip image

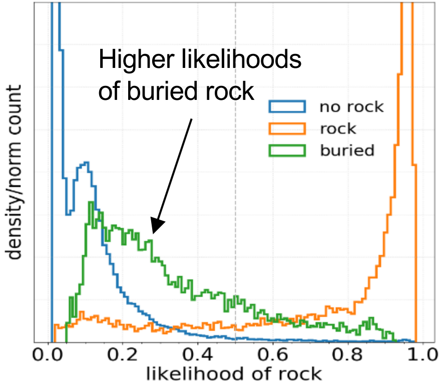


High slip image



Test error for various slip configurations





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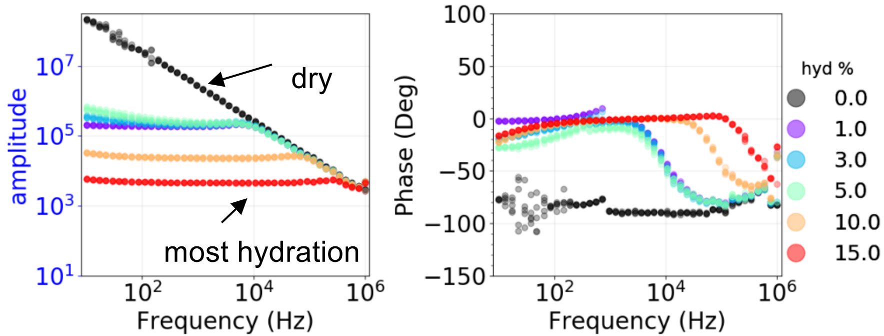
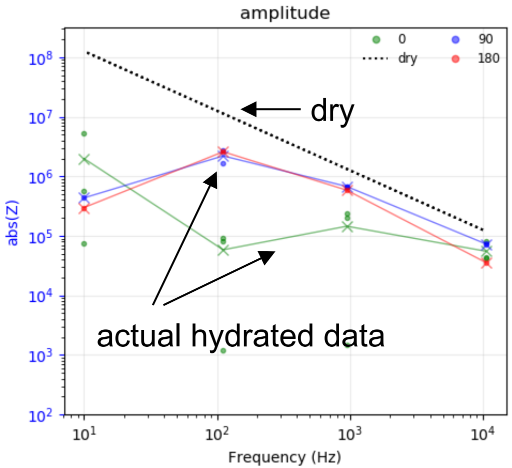
Results: hydration

Hydration classification is performed based on EIS sensor, which produces amplitude and phase of a signal:

- Data was collected in lab conditions, with static wheel experiments
- Discrete hydration levels set: 0, 1, 3, 5, 10, 15%
- Hydration accuracy -- **87-99%**

Hydration levels are clearly separated:





In-motion EIS experiment with **10%** hydration shows distinct moisture signature, however, data appears to be very noisy in general and requires good contact with the ground.

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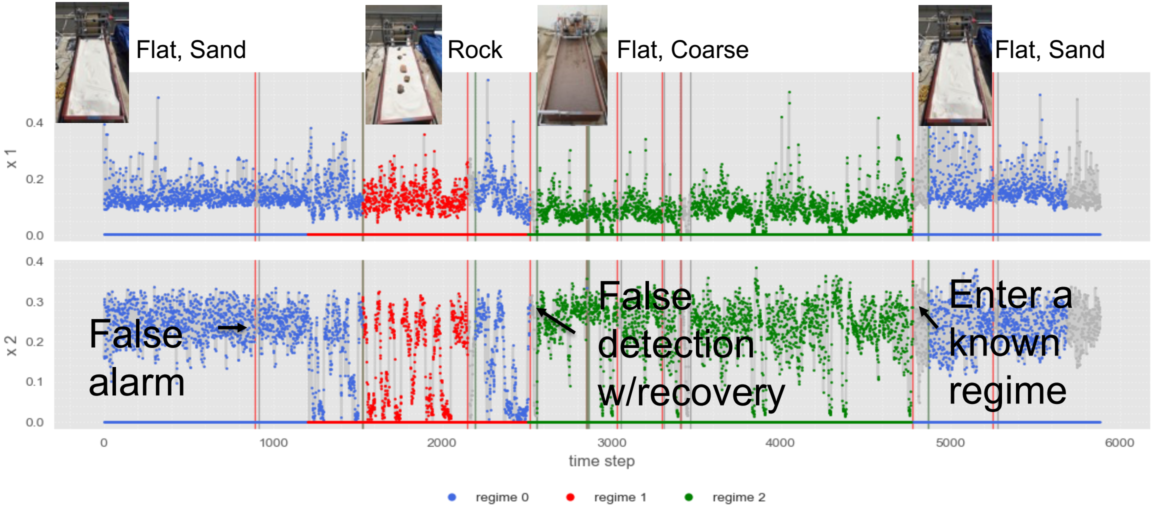
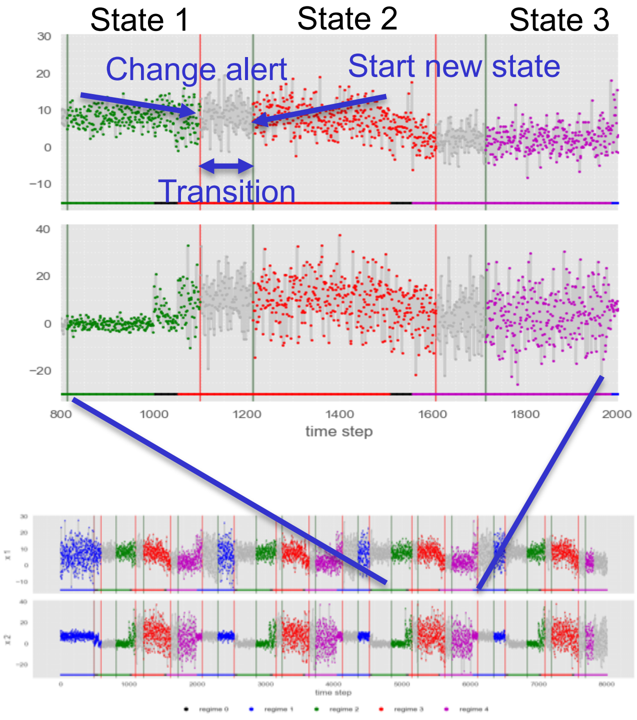
Unsupervised terrain detection

Monitor time series to determine high-level terrain state and changes:

- Are we seeing something we've seen before or **is this new**?
- **Prioritize** data/findings for onboard applications.
- Computationally **fast** and requires only a small amount of data to be held in memory.

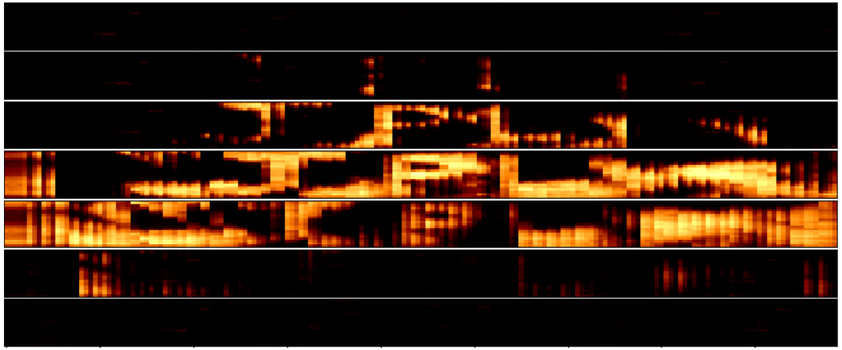




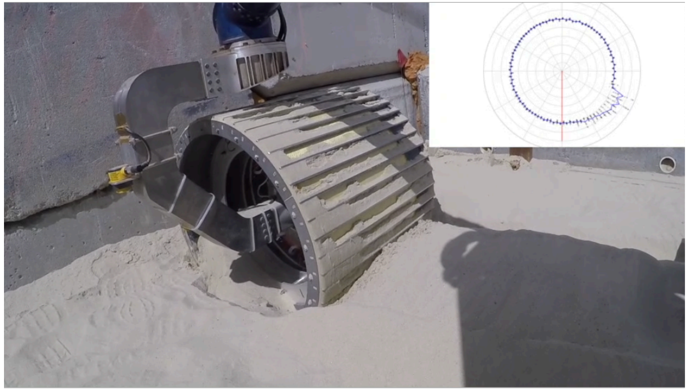
Simulated 4 time series states (colored)

Summary and future directions

- A low resolution 2D pressure sensor allows extraction of valuable information regarding the terrain.
- Simple and fast time series methods can capture the features of the terrain and the state of the wheel.
- Hydration levels can be detected, including while wheel is in motion with the EIS sensor.



- Implementation of developed software as part of an onboard system.
- A new, better tactile wheel and hardware that can represent deployment in real terrain.
- Various novel applications and infusions, e.g. ice roads/beachfront driving, Lunar/Martian wheels, new sensors (neutron spectrometer).



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